Socially Enabled Wireless Networks: Resource Allocation via Bipartite Graph Matching

Li Wang, Huaqing Wu, Wei Wang, and Kwang-Cheng Chen

ABSTRACT

The influence of social interactions among mobile devices and network components in wireless networks has attracted substantial attention due to its potential impact on resource allocation of spectrum and power in particular. We present an organized social graphical view on resource allocation and then extend to multi-objective resource allocation of wireless networks. We subsequently consider taking advantage of multi-dimensional resources, including radio resource, user behavior, and content characteristics, such that we can successfully integrate caching capability, interest similarity, and content popularity and distribution into wireless network design. As an illustration, device-to-device communications is utilized to form pairs and clusters of mobile devices regarding optimal resource matching via a bipartite graph. This socially enabled methodology highlights new potential to design wireless networks and 5G mobile communications.

INTRODUCTION

Modern design methodology of wireless networks proceeds on the ground of the Open Systems Interconnection (OSI) layer structure. A typical approach starts from a physical layer transmission mechanism, multi-access on a medium, and then networking algorithms and protocols. Such an approach is very reasonable, particularly when the traffic is connection-based such as voice calls, and can be extended to variable rate video and best effort data.

As the Internet and cloud computing have created tremendous services and applications, social media and the Internet of Things (IoT) supply major traffic for mobile wireless networks, which actually suggests a new paradigm in the design of wireless networks. As indicated in [1], the interplay of technological networks and social networks has not been fully exploited. It is also noted that any entities of probabilistic or dynamic relationship can be generalized into a social network. When social media and human-centric applications drive the progress of networking technology, the methodology to leverage social network analysis to design wireless networks is of particular interest but remains open [2]. In this article, we orient graph matching in social network analysis to systematically enhance the design of wireless networks, with focus on radio resource allocation.

Applying graph theory to resource allocation in a network is not a strange idea. However, this approach is scattered in the literature and mostly done in a rather ad hoc manner. In this article, we present a systematic approach of generalizing social networks and also apply graph theory for appropriate resource allocation in wireless networks, particularly by leveraging bipartite graphs. Our overall system scenario is depicted in Fig. 1, not targeting radio resource allocation directly according to only the air interface, but taking social interactions, caching capability, and interest similarity for users into account simultaneously. Later in this article, we elaborate more on content sharing and resource sharing in socially enabled wireless networks.

RESOURCE ALLOCATION VIA BIPARTITE GRAPH

Wireless physical radio resource can be considered jointly in the frequency and time domains. The traditional physical layer transmission, or *single-user PHY*, allows only one transmission at a certain time over a certain frequency band. Even in orthogonal frequency-division multiplexing (OFDM), adopted by IEEE 802.11a/g, all 48 data subcarriers are dedicated in each transmission. With the introduction of orthogonal frequency-division multiple access (OFDMA) in fourth generation Long Term Evolution (4G-LTE), also known as multi-user OFDM, we have entered the era of employing *multi-user PHY*; thus, radio resource is utilized by radio blocks in terms of frequency-time resource elements. Here, we introduce a systematic and generally

Li Wang and Huaqing Wu are with Beijing Key Laboratory of Work Safety Intelligent Monitoring, School of Electronic Engineering, Beijing University of Posts and Telecommunications.

Wei Wang is with Zhejiang University.

Kwang-Cheng Chen is with National Taiwan University.

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applicable way to abstract radio resource optimization and thus allocation in modern complex wireless networks.

As shown in Fig. 2, suppose there are M users who buffer or cache popular contents for content sharing with partners via wireless communications. Each user can select its partner based on whether the chosen partner has the desired (target) content it needs, whether the chosen partner can be trusted or tightly connected, and whether the allocated spectrum resource and channel state for the corresponding links are stable enough to support the whole data transmission, as shown in Fig. 1. All these demands can be satisfied by selecting appropriate partners, which is exactly a bipartite graph problem. The partner pairing problem is illustrated in Fig. 2a. More generally, the users we discuss could also be the base stations (BSs) or the operators. In these cases, the cell selection or operator selection can be addressed by bipartite graph matching as well.

Then suppose there are N partitioned units of radio resource that can be PHY time-frequency resource blocks, labeled $R_1, \ldots, R_N$, to support users $1, 2, 3, \ldots, M$. The communication or networking bandwidth demands are therefore represented by $a_1, a_2, \ldots, a_M$ (or $b_1, b_2, \ldots, b_M$). For user satisfaction, user i's bandwidth demand a_i can be assigned to one of the available radio resource units, say R_1, R_2, or R_3, as illustrated in Figs. 2b and 2c, which is exactly another bipartite graph. The resource allocation is therefore a bipartite graph matching that is well studied in graph theory, and [4] is one early example of applying such a concept. Similarly, the users here could be BSs or operators.

Let us use a new set of notations to study a bipartite graph representing a system. Suppose $\{S_1, S_1, \ldots, S_n\}$ is a collection of $n \geq 2$ finite nonempty sets. This collection is said to have a system of distinct representatives if there are n distinct elements $x_1, x_2, \ldots, x_n$ such that $x_i \in S_i$, $\forall i$. In other words, x_i is the representative of the set S_i. A condition that collections of sets contain a system of distinct representatives is known as Hall's theorem in graph theory.

Hall's Theorem

A collection $\{S_1, S_2, \ldots, S_n\}$ of n nonempty finite sets has a system of distinct representatives if and only if for each integer k with $1 \leq k \leq n$, the union of any k of these sets contains at least k elements.

Hall's theorem suggests that the identification of cluster leaders in a bipartite graph can be equivalent to resource allocation based on each entity's requirements. Computationally efficient algorithms have been widely investigated in the mathematical literature, including weighted bipartite graphs [3]. This remarkable theorem provides a sufficient condition for the existence of a perfect matching. The violation of its condition (e.g., two pairs after a selection algorithm may aim to use the same resource, resulting in violating the achievement of perfect matching and subsequent performance degradation) leads to performance degradation. Fortunately, Hall's theorem holds for most cases in wireless networks, and is successfully applied in many networking algorithms in engineering literature by satisfying the statistical performance constraints.

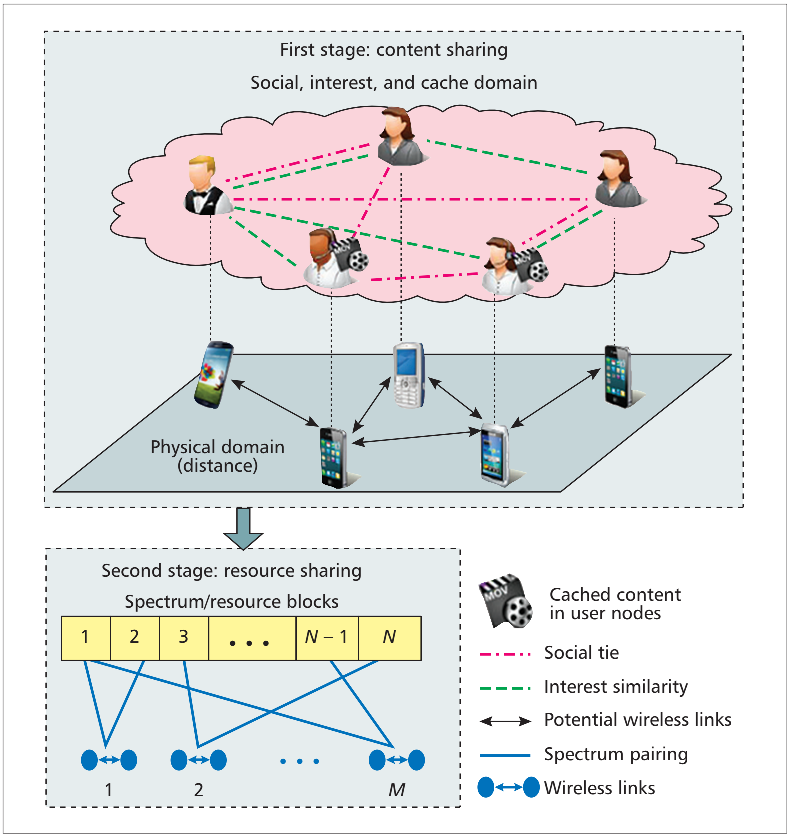

Figure 1. A hierarchical and multi-domain oriented graph matching framework. Both contents and radio resources could be considered as resources in general to design wireless networks.

Literature Survey

One of very early connections between bipartite graph and resource control in networks was reported in [4], which links the network control algorithms and the edge coloring algorithms for bipartite graphs. As a matter of fact, bipartite graph matching has been deeply studied and widely applied to discrete resource allocation in social economics for a long time [2, 5], while other typical applications include house assignment, hospital bed matching, and college admission/selection, among others.

In recent years, the bipartite graph has been utilized in several cases of radio resource allocation in wireless networks. To simultaneously consider both the bandwidth utilization and starvation problems, a bipartite graphical method was introduced to dynamic spectrum allocation in wireless mesh networks [6]. A remarkable idea, to construct a conflict graph to avoid interference, can be established during the process. Algorithms were developed in bipartite graph matching based on maximum cardinality or maximum weight [7]. For spectrum efficiency, maximum weighted graphical modeling is usually useful. Along the same thinking, optimal channel and relay assignment in a multi-pairing OFDM relay network can be translated into a maximum weighted bipartite matching problem [8]. It also

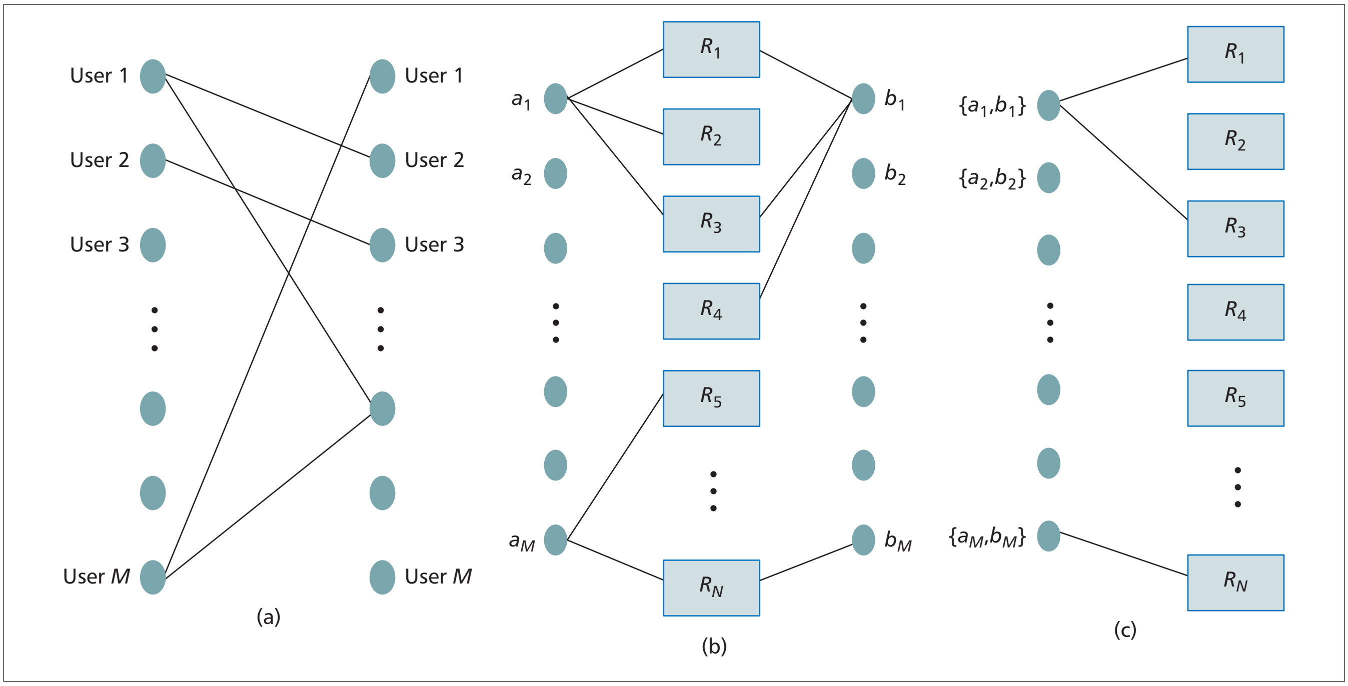

Figure 2. Multi-objective oriented bipartite graphs and evolving of concepts to facilitate: a) multi-dimensional partner selection; b) resource allocation via graph; c) regenerative bipartite graph.

implicitly suggests that multi-dimensional factors can be considered in the optimization of resource allocation.

Multi-Objective and Hierarchical Bipartite Graph Matching

Although techniques have been scattered in literature and summarized above, an effective methodology is crucial to achieve appropriate resource allocation in state-of-the-art complex wireless networks supporting diverse application scenarios, especially for cases taking social interaction into account. Starting from a straightforward extension using bipartite graph matching, we discuss multi-objective generalization of graph matching to fully utilize social networking. Furthermore, we propose a novel concept of hierarchical bipartite (HBP) to elaborate practical realization.

Multi-Objective Bipartite Graph Matching

An immediate extension of multi-objective bipartite graph matching is bandwidth aggregation, while modern mobile communications networks have to serve traffic ranging from social video and high-definition movies to IoT traffic of small packets that might require low-latency transportation. User traffic might require huge bandwidth in terms of multiple radio resource units, to satisfy either quality of service (QoS) or quality of experience (QoE). Since multi-objective resource allocation can be modeled as a new regenerative bipartite graph matching, as illustrated in Fig. 2, in which multiple repetitions are needed for ensuring allocation success.

According to graph theory, Hall's theorem guarantees the conditions of successful allocation. However, recent advances in networking suggest further dimensions of consideration in resource allocation, particularly in wireless networks. In particular, social characteristics for mobile users emerge to play a key role in wireless network design [9, 10]. Social-interaction-based resource allocation optimization becomes multi-objective, that is, maximizing the sum system capacity with different QoS constraints or minimizing the outage probability, which inspires generalizing the social graph theoretical resource allocation into multi-objective purposes as well. Furthermore, we can also target the secrecy rate of mobile users in the presence of eavesdroppers.

Luckily, it is rather straightforward to generalize bipartite graph matching to multi-dimensional matching. Suppose a user (or traffic) needs radio resource allocation by satisfying different design criteria, without loss of generality, a_1 and b_1. To achieve a_1, we create a bipartite graph, and similarly to achieve b_1, illustrated by Fig. 2. Different from earlier bipartite graph matching problems, a user or traffic can have multi-objective resource allocation, where the objectives may come from different criteria associated with each stream of traffic from a social networking perspective. We may create a multi-dimensional bipartite graph (Fig. 2b). If we collect all objectives together to form vectors of request, $\{a_m, b_m\}$ for user/traffic $m, 1 \le m \le M$, the candidate resource blocks must satisfy both criteria. For example, R_1, R_2, and R_3 satisfy a_1, and R_1, R_3, and R_4 satisfy b_1. The request vector $\{a_1, b_1\}$ for user/traffic 1 only connects to R_1 and R_3 (i.e., the intersection of sets formed by resource blocks matching both criteria, Fig. 2c). In this way, we can obtain a regenerative bipartite graph for multi-objective resource allocation; then existing allocation algorithms based on Hall's theorem can be extended in a straightforward way.

HIERARCHICAL BIPARTITE GRAPH MATCHING

In practice, various objectives determine different kinds of bipartite graph we should adopt. An unweighted bipartite graph can be adopted to achieve maximum cardinality, that is, maximizing the number of wireless links assigned spectrum resource for transmission. For weighted bipartite graphs, the weight of the edges can be defined differently for various objectives.

Homophily is widely known in social networks: users with similar interests or tight relationships are likely to have similar behavior, such as downloading the same popular contents. Users can select an appropriate partner that has the target content by considering multi-dimensional factors, such as the physical distance and social trust between different user nodes, and the cache capacity of user nodes. Then a user can obtain its need from its partner(s), which can significantly improve efficiency and offload from BSs. Afterward, wireless resource allocation can be carried out to assign proper resource blocks to maximize system performance.

Therefore, we propose the concept of HBP, which consists of upper layer bipartite for communication partner selection and lower layer bipartite for resource allocation. When it comes to the upper layer case, the benefit of caching for neighboring partners cannot be ignored. From the perspective of the upper layer, hit probability and access delay represent the weight when content sharing is taken into account. On the other hand, when it comes to the lower layer case, we can simply consider physical wireless resource allocation in wireless networks; thus, the weight can be the achievable data rate, secrecy rate, and outage probability of wireless links. Furthermore, the system performance can be measured by the weight of one particular edge or the sum weight by utilizing the maximum weighted bipartite matching.

In addition to the hierarchical bipartite graph described above, when users communicate with BSs directly rather than forming communication partners, the resource allocation can be accomplished by using one single bipartite considering multi-dimensional factors referring to Figs. 2b and 2c. In this case, we do not have to discuss the formation of a user partner, targeting the access time, hit probability, data rate, and so on, which represents a bipartite graph corresponding to Fig. 2a. However, we note that partner formation can be much more important and effective in some random cases or events, and can usually be ignored among tightly connected communities or societies.

HBP FRAMEWORK FOR SOCIALLY ENABLED WIRELESS NETWORKS

Recall that the social tie (relationship), interest similarities, caching capabilities, and physical distance among users can be represented by graphs, which are composed of nodes and edges among them. To reflect the efficient, accurate, and practical graph regarding multi-domain factors while avoiding unnecessary recomputations and energy consumption as much as possible, we conduct the methodology mentioned above in the physical, social, interest, and cache domains as shown in Fig. 3, in terms of the partner formation (e.g., pairing or clustering) and physical resource allocation for communication links, which are upper layer bipartite and lower layer bipartite, respectively.

According to Fig. 2c, with slight modification, we can obtain the ranking list of candidates for the partner finding case relating to Fig. 2a, and physical resources to different users or multiple preferred factors of specific users corresponding to Fig. 2b. To avoid re-computing for cases with different objectives, we can use the overlapped ranking list between them as our candidates, as shown in Fig. 2c. It is also suitable for cases when we consider time-variant conditions to reduce complexity and avoid redundancy in computing.

CONTENT-SHARING-ORIENTED UPPER LAYER BIPARTITE

Two devices within the maximum physical distance of each other can transmit data and form a communication pair (links or partners), which eventually establish a connected graph. Toward content sharing, in addition to the *physical distance*, it is worth considering the social and cache considerations jointly in the user pairing process. *Social ties* and *interest similarities* (common interests) ensure that the users who already have the desired contents would like to share their data with higher security. Note that social ties can be evaluated by social trust, as shown in Fig. 3, since trust and privacy are going to be more and more important for human society. *Cache capability* makes it possible for a user to cache more than the required data and improve the efficiency of content sharing. Considering these multiple effective factors that affect user pairing performance, we can target the objective of user pairing as data rate, cache hit probability, access delay, and many others.

WIRELESS-RESOURCE-SHARING-ORIENTED LOWER LAYER BIPARTITE

After the user pairing considering upper layer factors, we consider the wireless resource allocation for these constructed user pairs according to the lower layer factors, including the spectrum properties and social relationship. Different spectrum bands accommodate various transmission opportunities, propagation properties, and so on, which supply different communication bandwidth for the data transmission of user pairs. With limited wireless resources, spectrum efficiency can be improved by spatial reuse, where multiple user pairs share their resource. For efficient resource sharing, the mutual social relationship and interactions between user pairs that use the same wireless resource should also be considered. With tight social ties (high social trust) among user pairs using the same resource, it is possible to achieve more efficient resource sharing, such as efficient interference coordination among these user pairs, by leveraging their transmit power. For wireless resource sharing, in addition to the achievable data rate and system capacity, security is also of great importance. Hence, we can also consider security objectives

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(i.e., secrecy capacity or secrecy outage probability) for all the matched transmitter-receiver pairs.

Clustering Extension for Hierarchical Bipartite

In addition to pairing users, it is also necessary to divide the users into groups (clusters) regarding to social tie, interest similarity (common interest), caching ability, and computing capability as well, for sharing the same resources later. However, for the upper layer case (i.e., the 1st stage), the clustering case of taking multiple factors into consideration might be quite challenging since the utility of a user being added into or removed out of a cluster depends on all the other users' influence and willingness to share within the same cluster, and thus the edge weights of bipartite graph are generally not constants. On the other hand, for the lower layer case (i.e., the second stage), we not only need to pair the given spectrum resource with one single user but a number of clustered users instead. Different system reward metrics are considered (e.g., achievable network capacity, outage probability, energy efficiency, and secrecy-oriented metrics as well). That means, we also need take the co-channel interference among cluster users into account simultaneously, as shown in Fig 4. The clustering in Fig. 4 degenerates to a pairing problem when the number of members in cluster M drops to 1 (i.e., $K_m = 1$).

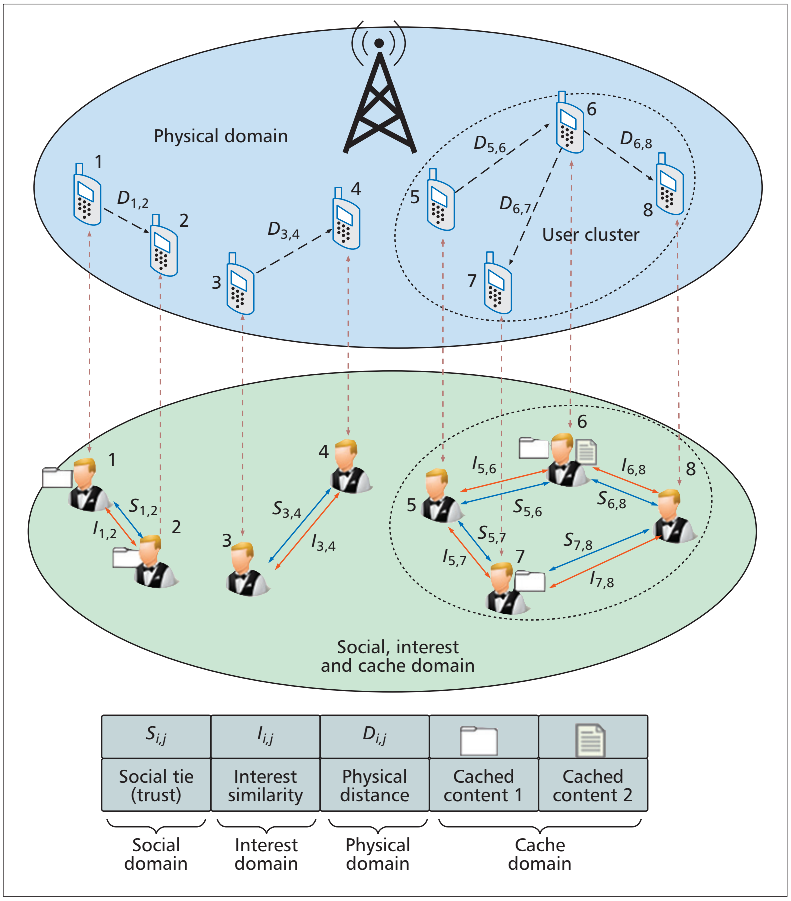

Figure 3. Multiple factors oriented users' pairing and clustering for the content sharing case: upper layer bipartite.

Weights for Resource Allocation via HBP

To establish the hierarchical bipartite of resource allocation, it is necessary to identify effective factors for content sharing and wireless resource sharing. With users' social interactions and effective physical communication, we would particularly like to include social trust, interest similarity, and cache capability in the HBP framework in terms of social ties and content caching.

Social-Tie-Driven Scenario

We start by defining graphs with different purposes to comprehend the relationship and consequent framework. A social graph is a connected graph that indicates the social ties among users who know each other in real life (e.g., family members, classmates, colleagues, and club members) or in social networking society (e.g., Facebook and LinkedIn). An interest graph indicates members' hobbies, interests, or individual needs. It can be generated by the new feeds that users follow, products that they purchase (e.g., on Amazon), movies or media that they prefer (e.g., ratings on YouTube), or survey information that they supply.

Social tie and interest similarity are simultaneously involved in the weights of resource allocation bipartite graphs, and will be of vital significance to better exploit contemporary social-network-based wireless communication.

In the upper layer bipartite of HBP, social ties bring trust in the real world into the weights for content sharing. It is probably more decent for privacy to share resources between users who are familiar with each other, which leads to a large weight in the bipartite graph. Users in the same society usually have similar interests, such as downloading the same popular dancing video for the members of one dance club. Taking social and interest graphs into account will potentially improve the security and success ratio and reduce the system cost for content sharing.

In the lower layer bipartite of HBP, social ties facilitate the cooperation of wireless resource sharing among user pairs that use the same resource, and thus improve system performance. User pairs with tight social ties have large weights for sharing the same resource.

Content-Caching-Driven Scenario

Traffic localization by distributed caching provides an efficient way to reduce the cost of content sharing, which is the core idea of content-centric networks (CCNs) [11]. As the storage sizes of wireless communication devices grow, the cache contents of a user includes not only his/her own pertinent data but also specifically required popular data cached for other users [12]. The benefits induced by caching the former data mainly depend on the similarity of individual interests or preference among devices for users, and that for the latter is affected by the cache capability of user devices.

Recall that in the interest graph concept defined above, users in the same society usually have similar interests. For example, the members of one dance club would like to download the same popular dancing video. For better content sharing, which users are selected to download this video from the server and cache it locally depends on the users' storage capability. Some user devices have stronger cache capability, so these corresponding users can cache more popular contents for sharing with other users.

Different from the social-tie-driven case, the cache contents affect the upper layer bipartite only. Cache content related to users' interests, content multiformity, and replica locations over the network topology should be taken into account in the weights of the upper layer bipartite graph to achieve maximum content hit probability and minimum content access delay [13].

HBP Graph Matching Implementation in Wireless Networks

According to the concept of HBP, the design and implementation of wireless networks can be composed of two steps (stages), which utilize the information from user partners and allocate wireless/radio resources, respectively.

In the first stage, regarding the exploitation of multiple domains, we establish user partners considering not only the physical distance but also the social interaction and interest similarity of mobile users in HBP, as shown in Fig. 3. Specifically, $s(m, n) \in [0, 1]$ and $c(m, n) \in [0, 1]$ are the social trust index and interest similarity between mobile users m and n, respectively. Furthermore, $r(m, n) \in [0, 1]$ can also represent caching capability for user m, the ratio of the cached content to the whole demand of its partner n.

After pairing the user partners, in the second stage, radio resource blocks should be assigned to those communication links to accomplish the data transmission and service requirements. Thus, the achievable data rate of communication link j between mobile users m and n using resource block i (spectrum) can be expressed as

$$R(m,n) = \sum_j q_{i,j} s_1(m,n) \cdot \log_2(1+\xi_j), \quad (1)$$

where $q_{i,j}$ is the matching indicator variable between resource block i and communication link j. $q_{i,j} = 1$ indicates that communication link j uses the resource block i; otherwise, $q_{i,j} = 0$. $s_1(m, n)$ denotes the union of social-oriented multi-factors between two mobile users who can potentially form a communication link, $s_1(m, n) = a \cdot s(m, n) + b \cdot c(m, n) + c \cdot r(\mathrm{m}, n)$, where a, b, c are constant weight parameters according to different factors, and a Œ $[0, 1]$, $b \in [0, 1]$, $c \in [0, 1]$, $a + b + c = 1$. ξ_j is the signal-to-interference-plus noise ratio (SINR) of communication link j.

To bring the critical security concern into this scenario, we can replace the data rate in Eq. 1 in favor of the secrecy rate for joint optimization of secrecy- and efficiency-oriented resource allocation. However, we omit the similar optimization equation because of length limitation.

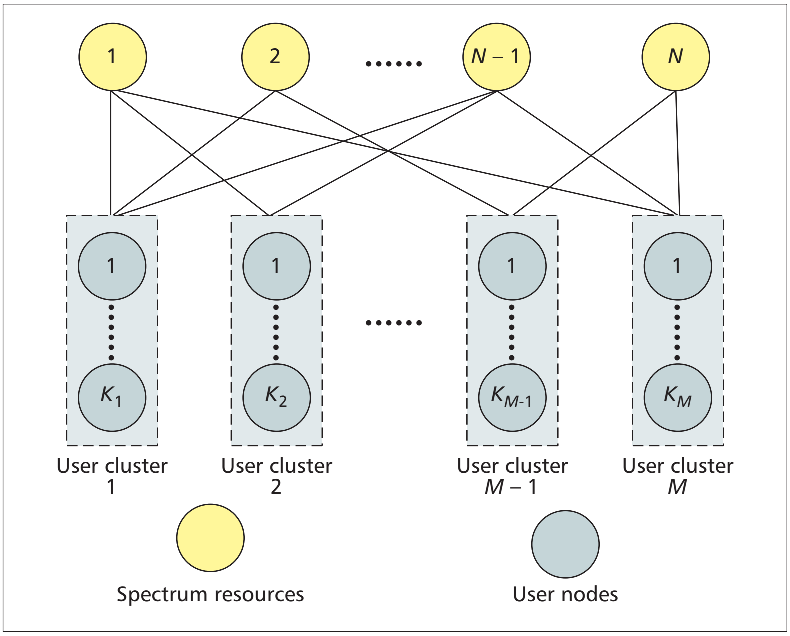

Figure 4. Resource sharing for user pairing and clustering: lower layer bipartite.

D2D Communications: An Illustration

In mobile social networks, device-to-device (D2D) communications have proven efficient for mobile services with high rate demands, such as video sharing and dissemination, since it can potentially establish direct links between proximity users without going through the BS.

We take D2D communications as an example to implement our generalized social enabled wireless network framework. Multi-dimensional generalization, discussed later, allows us to include energy efficiency, location, and radio range, and more relationships among devices in optimizing radio resource allocation. D2D underlay and overlay [14] are two typical modes in terms of different spectrum sharing. In D2D underlay, co-channel interference should be considered in addition to the D2D overlay cases. We note that the secrecy-oriented objectives are also applicable for D2D cases. Without loss of generality, we consider D2D underlay here as an illustration, which can be viewed as an extension of multi-pairing in wireless mesh networks. Therefore, after appropriate admission control and power control to form stable and reliable D2D pairs, maximum weighted bipartite matching was again employed to maximize overall network throughput [15]. Accordingly, Eq. 1 can be regarded as the achievable data rate of D2D link j formed by DUE m and n, sharing the resource of CUE i, and rewritten as

$$R(i,j) = s_2(i,j) \sum_j q_{i,j} s_1(m,n) \cdot \log_2(1+\xi_j^d), \quad (2)$$

where ξ_j^d is the SINR of D2D link j when it shares the same resource with CUE i. $q_{i,j}$ is the matching indicator variable between CUE i and D2D link j, $q_{i,j} = 1$ indicates that D2D link j

reuses the resource of CUE i; otherwise, $q_{i,j} = 0$. P_i^c and P_j^d are the transmit power of CUE i and the transmitter of D2D link j, respectively. Note that $s_2(i, j)$ represents the social trust between CUE i and D2D link j, which are sharing the same resource, that is, the probability that CUE i would be willing to share its resource with D2D link j.

Recall that we define stage 1 as the process of D2D partner selection regarding to high-layer preference factors, and stage 2 is defined as the procedure of CUE and D2D-link matching depending on wireless resource level. We shall discuss the achievable data rate for D2D links by taking different factors into consideration in stages 1 and 2, with different number of CUEs and D2D links, and their corresponding transmit power limitation.

For notational simplicity, we use PDO-1 and PDO-2 to denote the cases when considering factors in the physical domain only in stages 1 and 2, respectively. Similarly, MD-1 indicates that multi-domain factors are taken into account in stage 1, targeting physical distance, mutual social trust, interest similarity, and cache capability of DUEs. However, both MD-2-A and MD-2-E consider multi-domain factors, which are physical distance and social trust between CUEs and D2D links in stage 2. Furthermore, we use MD-2-A to indicate the case with accurate social trust between CUEs and D2D links, whereas social trust estimation error exists in MD-2-E.

For further analysis, we combine the cases discussed above, as shown in Fig. 5. For example, PDO-1 + MD-2-A implies that only physical domain factors are considered in stage 1, and multi-domain factors are taken into consideration in stage 2 with accurate social trust. Accordingly, the closest M pairs of DUEs are chosen to form D2D links in the PDO-1 + MD-2-A strategy. However, the MD-1 + MD-2-A strategy forms D2D links with multiple objective preferences, referring to Eq. 1. Furthermore, pairwise power optimization carries out the maximization of $R(i, j)$ after the D2D pairing, before optimizing the overall sum data rate of D2D links via optimal matching.

Figure 5 shows that the sum rate of the system grows with the increasing number of CUEs and successful pairing D2D links, because more D2D links and CUEs make it possible for better resource allocation, thereby leading to larger sum data rate. We find that the MD-1 + MD-2-A strategy achieves a significantly higher rate compared to PDO-1 + MD-2-A, since the latter has higher probability of choosing D2D users with low $s_1(m, n)$, thereby making it difficult to guarantee the value of $R(i, j)$. To overcome this drawback, the MD-1 + MD-2-A strategy chooses D2D users by considering both physical and social-oriented (multiple) factors to form D2D links, which ensures the superiority of system performance to a large extent.

Different from Fig. 5, Fig. 6 demonstrates that larger $P_{i,\max}^c$ and $P_{j,\max}^d$ allow each pair of D2D links to reach a higher rate and subsequently a higher sum data rate. It can also be easily observed from Fig. 6 that MD-1 + MD-2-A and MD-1 + MD-2-E outperform MD-1 + PDO-2, because the matching results in MD-1 + PDO-2 may suffer from poor utilization of social information, further resulting in the less favorable system reward, whereas MD-1 + MD-2-A and MD-1 + MD-2-E give full consideration to the social trust between CUEs and D2D links. Thus, the matching result guarantees the maximization of the achievable sum data rate and relative rate for D2D links as well. In addition, the gap between those curves that are holding estimated social trust and accurate parameters is not huge, and can be ignored by considering multiple social oriented factors. In other words, the robustness of the multi-domain strategy outweighs that of the MD-1 + PDO-2 strategy.

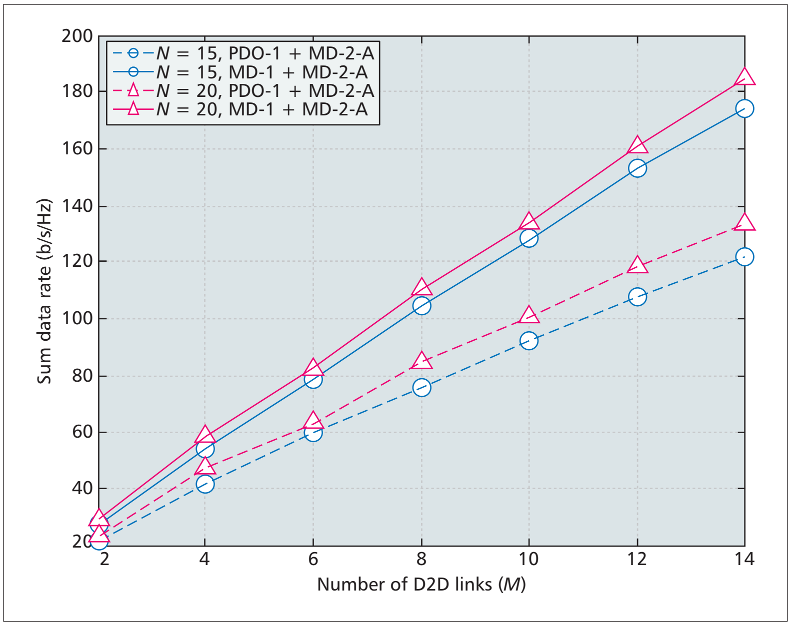

Figure 5. Sum system data rate with different number of CUEs and D2D links. We consider a single cell of radius R, where N conventional CUEs and M D2D links are uniformly distributed in the cell with the radius of R = 300 m. The noise power for each channel is assumed as σ_N^2 = –96 dBm. The distance between two DUEs to form a potential D2D link is less than the maximum D2D tolerant distance, $d_{\max}^d$ = 30 m, and CUE i can only be regarded as a resource sharing candidate of D2D link j if the corresponding distance is no less than the minimum reuse distance depending on the maximum tolerant co-channel interference, $d_{\min}^c$ = 100 m. Note that the maximum transmit power of CUEs and D2D transmitters are $P_{i,\min}^c$= 24 dBm and $P_{j,\min}^d$ = 19 dBm, respectively.

Conclusions

In this article, we have presented a novel graph-theoretical framework for resource allocation by exploiting the inherent interplay between social networks and wireless communications. We have provided a systematic approach for multi-objective optimization and then applying bipartite matching to enhance the design of wireless networks. Specifically, we propose hierarchical bipartite-based pairing and clustering by jointly considering multi-dimensional factors in terms of two stages, selecting the partner first and optimizing the resource allocation after.

Numerical results have demonstrated the merits of our proposed concept. Further investigations remain open, such as improving system robustness, since the key factors considered for resource allocation and content sharing can be time varying and prone to estimation errors in wireless networks.

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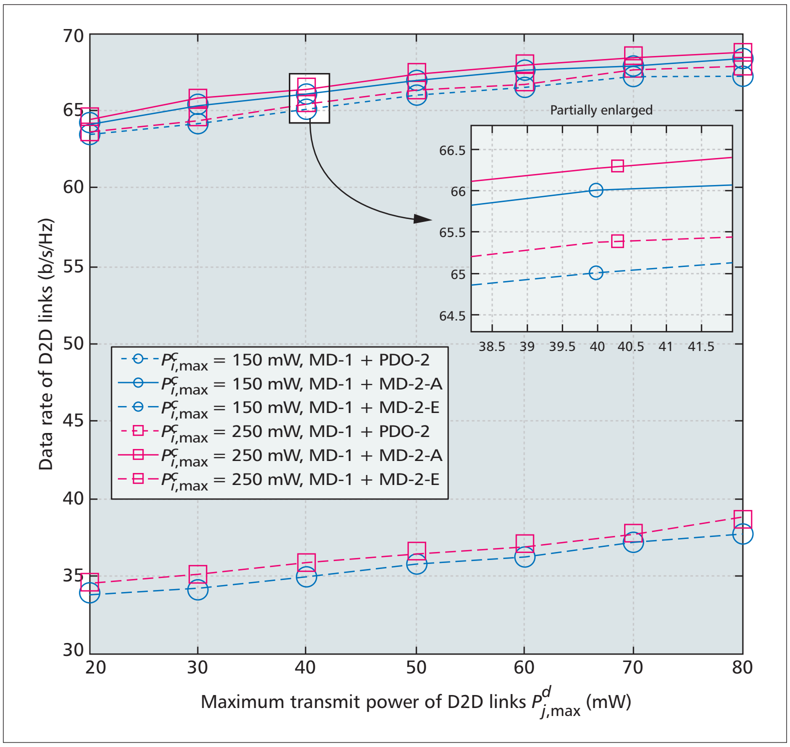

Figure 6. Sum data rate for D2D links with different maximum transmit power of CUEs and D2D transmitters.

Biographies

Li Wang [S'08, M'14] is an associate professor in the School of Electronic Engineering, Beijing University of Post and Telecommunications (BUPT), where she leads the Lab of High Performance Computing and Networks. She received her Ph.D. degree in 2009 from BUPT. She received the 2013 Beijing Young Elite Educator for Higher Education Award. From December 2013 to January 2015, she held a visiting research appointment at the School of Electrical and Computer Engineering at Georgia Tech, Atlanta. From August 2015 to November 2015, she was a guest researcher with the Department of Signals and Systems at Chalmers University of Technology, Gothenburg, Sweden. Her research interests include wireless networking, secure communications, device-to-device communication systems, and peer-to-peer networks. She has served or is serving on the Technical Program Committees of IEEE CCNC 2009, IEEE CCNC 2010, IEEE WCSP 2013, IEEE GLOBECOM 2014, IEEE WCNC 2015 , IEEE ICC 2015, IEEE ICNC 2015, IEEE ICCC 2015, IEEE GLOBECOM 2015, IEEE ICNC 2016, IEEE ICC 2016, and so on.

Huaqing Wu [S'15]reveived her Bachelor's degree from BUPT) in 2014. Since 2014, she has been pursuing graduate studies at BUPT. Her research interests include wireless networking, secure communications, and device-to-deveice communication systems.

Wei Wang [S'08, M'10, SM'15] received his B.S. and Ph.D. degrees from BUPT in 2004 and 2009, respectively. Currently, he is an associate professor with the Department of Information Science and Electronic Engineering, Zhejiang University, China. From September 2007 to September 2008, he was a visiting student at the University of Michigan, Ann Arbor. From February 2013 to February 2015, he was a Hong Kong Scholar with the Hong Kong University of Science and Technology. His research interests mainly focus on cognitive radio networks, green communications, and radio resource allocation for wireless networks.

Kwang-Cheng Chen [M'89, SM'94, F'07] is the Distinguished Professor, Graduate Institute of Communication Engineering, National Taiwan University. He has received a number of awards, including the 2011 IEEE ComSoc WTC Recognition Award, 2014 IEEE Jack Neubauer Memorial Award, and 2014 IEEE ComSoc AP Outstanding Paper Award, and has co-authored a few award-winning papers published in IEEE ComSoc conferences. His research interests include wireless communications, social networks and network science, and data analytics.